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AI–Supported Clinical Decision-Making in Recovery-Oriented Forensic and Addiction Psychology: A Transdiagnostic and Neurobehavioral Framework

Department of Research, Bout Me Healing

Author: Cice Rivera

Co Author:: Evly Pacheco

Contributor: Neza Camacho

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ABSTRACT

Recovery-oriented paradigms have significantly transformed contemporary mental health practice by prioritizing autonomy, resilience, and long-term psychosocial functioning over symptom reduction alone. Within forensic psychology and substance use disorder (SUD) treatment, clinicians face complex challenges involving risk assessment, relapse prevention, and ethical responsibility. Concurrently, advances in artificial intelligence (AI) have introduced new methodologies for clinical training, behavioral prediction, and decision support. This research presents an integrated, transdiagnostic framework positioning emotional dysregulation as a central mechanism underlying forensic risk behavior and substance use relapse. Drawing from neurocognitive, behavioral, and applied clinical research, this research examines how AI technologies, including machine learning, natural language processing, and digital phenotyping can enhance clinical decision-making, training, and early intervention. While AI offers substantial promise in improving precision and efficiency in clinical practice, its implementation requires careful ethical oversight, transparency, and adherence to professional standards. The integration of AI into recovery-oriented forensic and addiction psychology reflects a paradigm shift toward interdisciplinary, data-informed practice that remains grounded in human-centered clinical expertise.

Introduction

The evolution of mental health care toward recovery-oriented frameworks reflects a broader shift in psychological theory and clinical practice. Rather than conceptualizing individuals solely through diagnostic pathology, recovery models emphasize personal agency, resilience, and the capacity for meaningful social reintegration (Anthony, 1993). This paradigm shift is particularly significant within forensic psychology, where clinicians operate at the intersection of therapeutic care and legal accountability. For example, forensic clinicians are frequently tasked with evaluating whether individuals with histories of violent behavior and co-occurring mental health conditions can safely re-enter the community. Such decisions require not only risk assessment but also a nuanced understanding of emotional stability, environmental stressors, and behavioral regulation.

A parallel complexity exists within substance use disorder treatment. Despite advances in pharmacological and psychosocial interventions, relapse remains a persistent and defining characteristic of addiction (Larimer et al, 1999). Emotional dysregulation has consistently been identified as a primary contributor to relapse, particularly in response to stress, interpersonal conflict, and negative affective states such as anxiety, anger, and depression (Hand et al, 2024). These overlapping challenges highlight a shared clinical issue: decision-making under conditions of uncertainty, where risk is dynamic, multifactorial, and influenced by internal and external variables. Artificial intelligence offers a potential augmentation to this process by enhancing the detection of behavioral patterns, improving predictive accuracy, and supporting clinical training. However, AI must be conceptualized as a supplementary tool that enhances, rather than replaces, clinical judgment and ethical reasoning.

Recovery-Oriented Frameworks in Forensic and Clinical Contexts

Recovery-oriented frameworks emphasize individualized, strengths-based approaches to mental health care. Within forensic settings, this approach represents a shift from traditional models focused primarily on containment and risk management toward more holistic strategies that incorporate rehabilitation and reintegration (Drennan & Alred, 2012). For example, recovery-oriented forensic programs often include structured therapeutic interventions, vocational training, and psychosocial rehabilitation aimed at improving emotional regulation, interpersonal functioning, and long-term stability. Evidence suggests that such approaches can enhance treatment engagement and reduce recidivism (Simpson & Penney, 2018).

Similarly, in addiction treatment, recovery models extend beyond abstinence to include improvements in quality of life, emotional functioning, and social reintegration. Individuals are supported in developing adaptive coping strategies to manage high-risk situations and emotional triggers. Across both domains, emotional regulation emerges as a central clinical target. Deficits in emotional regulation contribute not only to relapse in substance use disorders but also to behavioral dyscontrol in forensic populations, reinforcing the need for integrated treatment approaches.

Emotional Dysregulation as a Transdiagnostic Mechanism

Emotional dysregulation can be understood as

a comprehensive meta-analysis involving 189 studies and 78,733 participants found strong associations between emotional dysregulation and substance-related and behavioral addictions (González-Roz et al, 2024). Neurobiological research provides insight into this relationship. Impairments in prefrontal cortical functioning, particularly in regions responsible for executive control, reduce the ability to regulate emotional responses generated by limbic structures such as the amygdala (Hand et al., 2024). This imbalance contributes to heightened emotional reactivity, impulsivity, and impaired decision-making. For example, during withdrawal states, individuals often experience intense negative emotional states, which reinforce substance use through negative reinforcement mechanisms. In forensic populations, similar dysregulatory processes may manifest as impulsive aggression, difficulty managing frustration, and increased vulnerability to environmental stressors. These findings suggest that relapse and recidivism are not isolated phenomena but rather parallel expressions of underlying deficits in emotional regulation and behavioral control.

Relapse Prevention Strategies

Marlatt and Gordon's cognitive-behavioral model of relapse prevention provides a foundational framework for understanding substance use relapse (Larimer et al, 1999). The model shows high-risk situations, coping deficits, and maladaptive cognitions as key factors of relapse. For example, an individual experiences interpersonal conflict with emotional distress, reduced coping capacity, and increased likelihood of substance use. Negative emotional states such as anger, anxiety, and boredom are consistently associated with the highest relapse rates.

Mindfulness-based relapse prevention (MBRP) extends this framework by integrating mindfulness practices to enhance emotional awareness and regulation. Research demonstrates that MBRP reduces substance use, cravings, and psychological distress (Bowen et al, 2014; Mendes et al, 2021). Individuals trained in mindfulness techniques are able to observe internal experiences without engaging in automatic behavioral responses. In forensic contexts, similar principles apply through structured risk management approaches that emphasize identifying triggers, enhancing coping skills, and improving behavioral regulation. Interventions targeting impulse control and emotional regulation are central to reducing recidivism risk.

Artificial Intelligence in Clinical Training and Decision-Making

Artificial intelligence introduces advanced analytical capabilities that can significantly enhance clinical training and decision-making processes. Machine learning algorithms are capable of analyzing large and complex datasets to identify patterns that may not be readily observable through traditional methods. For example, AI-driven simulation platforms can provide clinicians with realistic forensic case scenarios, allowing for repeated practice in risk assessment, ethical decision-making, and crisis intervention. These simulations create opportunities for experiential learning in controlled environments.

In addiction treatment, machine learning models

have demonstrated the ability to predict relapse using longitudinal data on mood, cognition, and craving (Lauvsnes et al, 2022). Notably, variability in craving, rather than static levels has been shown to be a significant predictor of relapse. Interpretable AI models, such as those utilizing SHAP analysis, enable clinicians to understand how specific variables contribute to predictive outcomes (Xu et al, 2025). This transparency is important for integrating AI into clinical practice in an ethical manner.

Additionally, natural language processing (NLP) techniques have been used to analyze linguistic patterns in social media and clinical data, demonstrating predictive validity for treatment outcomes (Curtis & Giorgi, 2023). These tools offer new avenues for identifying early indicators of relapse risk and treatment disengagement.

Digital Phenotyping and Real-Time Monitoring

Digital phenotyping represents a significant advancement in the application of AI to mental health care. By collecting real-time behavioral data through smartphones and wearable devices, clinicians can monitor changes in mood, activity levels, and social engagement. For example, decreased mobility, disrupted sleep patterns, and reduced communication frequency may signal increased psychological distress or relapse risk. These continuous data streams allow for more dynamic and ecologically valid assessment compared to traditional episodic evaluations. This approach facilitates intervention, enabling clinicians to respond to early warning signs before a full relapse or behavioral escalation occurs. However, it also raises important ethical concerns related to privacy, consent, and data security.

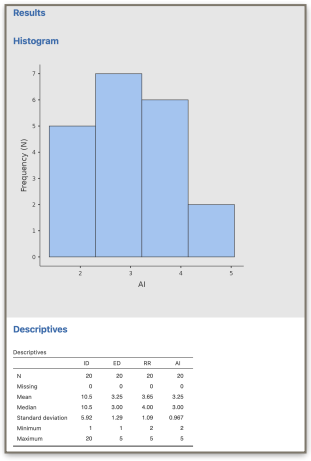
Ethical and Clinical Considerations

The integration of AI into forensic and clinical psychology raises complex ethical and legal issues. Data privacy is of particular concern given the sensitive nature of mental health information. Ensuring informed consent and secure data handling is an important component. Algorithmic bias presents another significant challenge. AI systems trained on historically biased datasets may present with inequities in risk assessment, within forensic populations. This emphasizes the importance of ongoing evaluation and validation of AI tools. Transparency and interpretability are critical for maintaining trust in AI-assisted decision-making. Clinicians must retain responsibility for interpreting and applying AI-generated insights within the broader clinical context.

Results

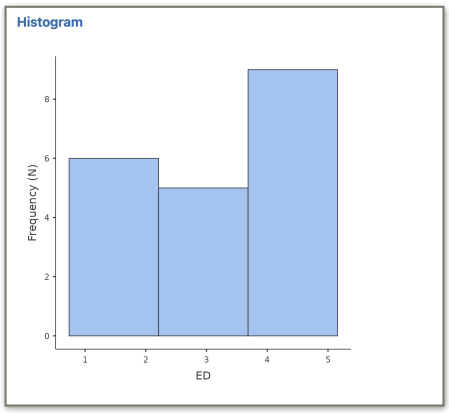
Descriptive statistics were computed for all study variables. For the participant identifier (ID), values ranged from 1 to 20, with a mean of M = 10.50 and a standard deviation of SD = 5.92. While ID was included for organizational purposes, it was not used in inferential analyses.

Table 1



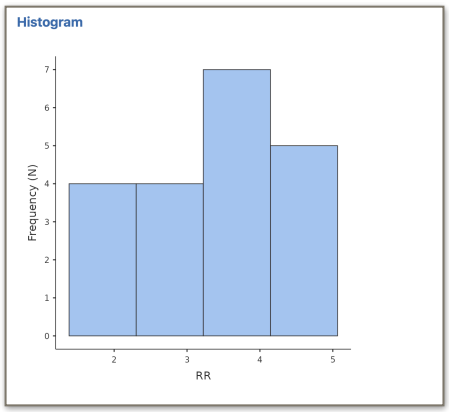
For ED, scores ranged from 1 to 5 with no missing data (N = 20). The mean ED score was M = 3.25 with a standard deviation of SD = 1.29, indicating moderate variability across participants.

Figure 1



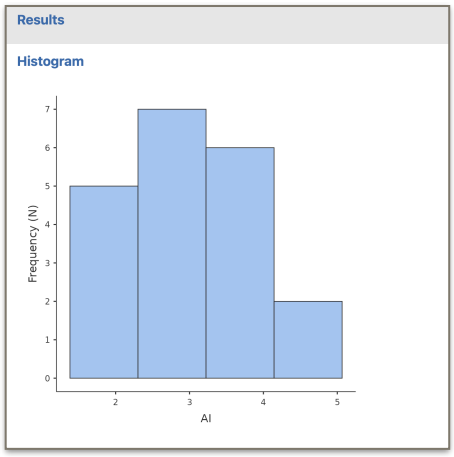
For RR, scores ranged from 2 to 5 with no missing data (N = 20). The mean RR score was M = 3.65, with a standard deviation of SD = 1.09, suggesting relatively moderate-to-high levels across the sample.

Figure 2



For AI, scores ranged from 2 to 5 with no missing data (N = 20). The mean AI score was M = 3.25, with a standard deviation of SD = 0.97, indicating moderate responses with slightly lower variability compared to RR and ED.

Figure 3



Visual inspection of histograms for ED, RR, and AI indicated distributions that were generally consistent with approximate normality, with no extreme skewness or outliers observed.

Overall, descriptive results suggest moderate levels across all primary constructs, with RR demonstrating slightly higher central tendency compared to ED and AI.

Discussion

Overall, the findings from this preliminary dataset suggest moderate levels of Emotional Dysregulation (ED), Recovery Readiness (RR), and AI Integration (AI) within the sample. RR demonstrated the highest mean score relative to ED and AI, indicating slightly elevated recovery-oriented readiness among participants. ED and AI showed comparable mean scores, suggesting similar central tendencies across emotional regulation and perceived AI integration within the decision-support framework.

Variability across all measures was moderate, with ED showing the greatest dispersion and AI demonstrating the least variability. This pattern suggests more consistency in AI-related responses, while emotional regulation responses were more heterogeneous across participants.

Taken together, these results provide preliminary quantitative support for examining the relationship between emotional regulation processes, recovery readiness, and AI-supported clinical decision-making. The observed distribution patterns and variability indicate that the dataset is suitable for further inferential analysis, including correlation testing, within a recovery-oriented and technology-assisted clinical framework.

Future research should focus on evaluating the effectiveness of AI-assisted interventions and training programs within forensic and addiction settings. Longitudinal studies examining clinical outcomes, decision accuracy, and patient engagement will be fundamental. Interdisciplinary collaboration among psychologists, data scientists, and legal professionals will play a critical role in developing ethical and effective AI applications. Additionally, professional organizations may establish guidelines to regulate the use of AI in clinical and forensic contexts.

Conclusion

This research presents an integrated, transdiagnostic framework linking forensic psychology and substance use treatment through the shared mechanism of emotional dysregulation. Recovery-oriented and relapse prevention models converge in their emphasis on enhancing emotional regulation and adaptive functioning. Artificial intelligence offers powerful tools to support this process through predictive modeling, behavioral analysis, and simulation-based training. However, its implementation must remain grounded in ethical principles, clinical expertise, and human-centered care. Ultimately, the future of clinical practice lies in the integration of technological innovation with evidence-based psychological frameworks, enabling more precise, responsive, and effective interventions across complex mental health populations.

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